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Using Support Vector Machine Method to Improve Company Performance Management

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Abstract

Purpose: To explore the application prospect of support vector machine (SVM) in supply chain management and its practical application in supply chain performance evaluation practice. **Research design, data and methodology:** This paper establishes the performance evaluation index system of supply chain management according to the balanced scorecard (BSC) theory, and establishes the SVM model of supply chain management performance evaluation based on the SVM principle. **Results:** The performance evaluation results of the supply chain of an electric power equipment Co., Ltd. in Harbin established by using the model are consistent with the actual situation, which indicates the nature and accuracy of the possible reflection of the established supply chain performance evaluation model. **Conclusions:** The results show that SVM model can be used to evaluate enterprise supply chain management performance indicators, and can improve enterprise supply chain management performance, thus demonstrating the effectiveness of the model.

Keywords: Support vector machines, Performance index, Supply chain management, Business Environment

JEL Classification Code: M31, M41, M50

1. Introduction

With the development of global economic integration and the intensification of market competition, enterprises have long been focusing on the supply chain management mode. The operation of supply chain has a significant impact on the interests of enterprises. Effective supply chains can boost an enterprise's competitiveness by lowering operating expenses, boosting revenue, and enhancing operational effectiveness. An essential component of supply chain management is performance evaluation, which enables prompt comprehension of supply chain operation, identification of operational gaps, and adoption of remedial actions. The performance evaluation of supply chain is a kind of supervision and incentive mechanism, which plays an important role in promoting the establishment of efficient cooperative relationship between supply chain node enterprises. As enterprises pay more attention to supply chain management, supply chain performance evaluation becomes more refined. It is necessary to explore a supply chain performance evaluation model suitable for small samples to

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evaluate supply chain performance in real time, so as to provide scientific basis for enterprises to improve supply chain management efficiency.

Scholars have carried out a wealth of research on supply chain performance evaluation, but the current research mainly uses AHP, DEA, expert system, mathematical programming, system simulation and other methods. These evaluation methods are more subjective. In addition, some scholars use neural network algorithm to evaluate supply chain performance.

Support vector machines are seen by many as the answer to a number of domains that need some form of artificial intelligence (Hong & Hales, 2021; Chauhan, Dahiya, & Sharma, 2018; AlBadani, Shi & Dong, 2022; Mustafa & Mohsin, 2021). Indeed, their convincing performance in terms of speed and accuracy in predicting the trends in financial markets (Zhao & Li, 2022), recognizing hand-written characters (Rana Vaidya & Gupta, 2022), or detecting plastic explosives in airport luggage (Akcay & Breckon, 2022), has given it a publicity which rival AI techniques find difficult to match. Not surprisingly, this has inevitably created certain misconceptions about the capability of support vector machines (Yao et al., 2022). This paper gives a general introduction to support vector machines and then examines performance index in supply chain management. Considering the advantages of SVM algorithm, this paper proposes to use support vector machine method to evaluate supply chain performance, and incorporate balanced scorecard for index input to supplement the shortcomings of other evaluation methods.

This paper consists of four sections. Section 2 introduces the concept of the balanced scorecard and give an index system for evaluating the performance of supply chain management. Section 3 provides the basic concept of Support Vector Regression and its applications in performance assessment. Section 4 discusses the experiment and comparisons, followed by the conclusions drawn from this study in the last section. The research conclusion of this article provides a methodological basis and theoretical support for enterprises to improve supply chain management performance.

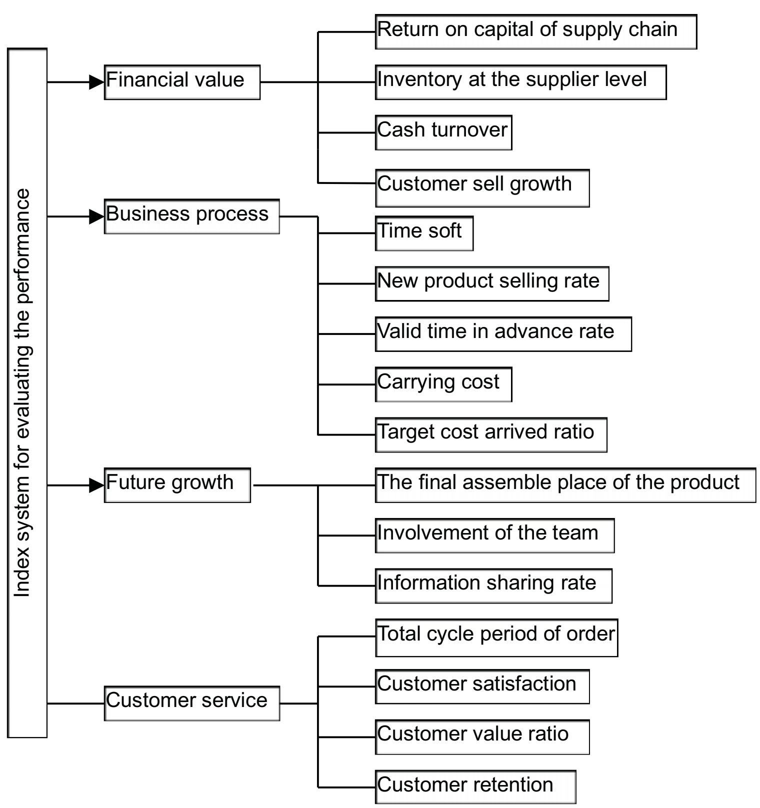

Figure 1: Index System for Evaluating the Performance of the Supply Chain

2. An Index System for Evaluating the Performance of Supply Chain Management

In the 1990s, Kaplan and Norton invented the balanced score-card. Their idea was that the evaluation of a company should not be restricted to the traditional financial performance measures but should be supplemented with measures concerning customer satisfaction, internal processes, and the ability to innovate. Results achieved within the additional perspectives to ensure future financial results. Kaplan and Norton proposed a three layered structure for the four perspectives: mission (to become the customers' most preferred supplier), objectives (to provide the customers with new products) and measures (to increase percentage of turnover generated by new products). To put the BSC to work, companies should translate each of the perspectives into corresponding metrics and measures that assesses the current situation. These assessments must be repeated periodically and have to be confronted with the goals that must be set beforehand. At first, the BSC is used as a performance measurement system and a planning and control device. Later on, some companies moved beyond this early vision of the scorecard. They discovered that the measures on a balanced scorecard can be used as the cornerstone of a management system that communicates strategy, aligns individuals and teams to the strategy, establishes long term strategic targets, aligns initiatives, allocates long and short term resources, and provides feedback and learning about the strategy.

An index system for evaluating the performance of supply chain management is set up according to the theory of balanced scorecard in this paper.

The balanced scorecard is used in evaluating the performance of supply chain management, and set up the index system in four perspectives: financial value, business process, future growth, customer.

3. The Proposed Support Vector Regression Algorithm

To look at a set of training data $\{(x_1, y_1),...,(x_\ell, y_\ell)\}$, where each $x_i \subset R''$ denotes the input space of the sample and has a corresponding target value $y_i \subset R$ for i=1, …, l where l corresponds to the size of the training data[12].The idea of the regression problem is to determine a function that can approximate future values accurately.

The generic SVR estimating function takes the form:

$$f(x) = (w \cdot \Phi(x)) + b \tag{1}$$

where $w \subset R^n$, $b \subset R$ and Φ denotes a non-linear transformation from R^n to high dimensional space. The goal of the paper is to find the value of w and b such that values of x can be determined by minimizing the regression risk:

$$R_{reg}(f) = C\sum_{i=0}^{\ell}\Gamma(f(xi) - yi) + \frac{1}{2}\|w\|^2 \tag{2}$$

where $\Gamma(\cdot)$ is a cost function, C is a constant, and vector w can be written in terms of data points as:

$$w = \sum_{i=1}^{\ell}(\alpha_i - \alpha_i^*)\Phi(x_i) \tag{3}$$

By substitution of equation (3) in equation (1), the generic equation can be rewritten as:

$$\begin{aligned} f(x) &= \sum_{i=1}^{\ell}(\alpha_i - \alpha_i^*)(\Phi(x_i)\cdot\Phi(x)) + b \\ &= \sum_{i=1}^{\ell}(\alpha_i - \alpha_i^*)k(x_i, x) + b \end{aligned} \tag{4}$$

In equation (4), the dot product can be replaced with function $k(x_i, x)$, known as the kernel function. Kernel functions enable dot product to be performed in high-dimensional feature space using low dimensional space data input without knowing the transformation Φ. All kernel functions must satisfy Mercer’s condition that corresponds to the inner product of some feature space. The radial basis function (RBF) is commonly used as the kernel for regression:

$$k(x_i, x) = \exp\left\{-\gamma|x - x_i|^2\right\} \tag{5}$$

Some common kernels are shown in Table 1. The paper has experimented with these three kernels.

(1) Polynomial kernel of order p: $k(x,x^*)=(1+x^T x^*)^p$

(2) RBF-kernel: $k(x,x^*) = \exp(-\frac{\|x - x^*\|_2^2}{2\sigma^2})$

(3) Hyperbolic kernel: $k(x,x^*) = \tanh(\beta x^T x^* + \kappa)$

The ε-insensitive loss function is the most widely used cost function.. The function is in the form:

$$\Gamma(f(x) - y) = \begin{cases} |f(x) - y| - \varepsilon, & for \quad |f(x) - y| \geq \varepsilon \\ 0 & otherwise \end{cases} \tag{6}$$

By solving the quadratic optimization problem in (7), the regression risk in equation (2) and the ε-insensitive loss function (6) can be minimized:

$$\frac{1}{2}\sum_{i,j=1}^{\ell}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)k(x_i, x_j) - \sum_{i=1}^{\ell}\alpha_i^*(y_i - \varepsilon) - \alpha_i(y_i + \varepsilon)$$

subject to

$$\sum_{i=1}^{\ell}\alpha_i - \alpha_i^* = 0, \quad \alpha_i, \alpha_i^* \in [0, C] \tag{7}$$

The Lagrange multipliers, α_i, α_i^*, represent solutions to the above quadratic problem that act as forces pushing predictions towards target value y_i. Only the non-zero values of the Lagrange multipliers in equation (7) are useful in forecasting the regression line and are known as support vectors. For all points inside the ε-tube, the Lagrange multipliers equal to zero do not contribute to the regression function. Only if the requirement $|f(x) - y| \geq \varepsilon$ (See Figure 1) is fulfilled, Lagrange multipliers may be non-zero values and used as support vectors.

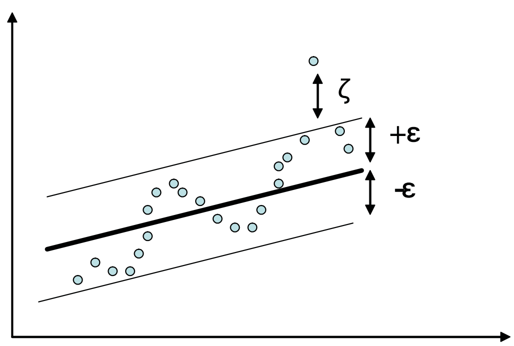

Figure 2: Support vector regression to fit a tube with radius to the data and positive slack variables ζ measuring the points lying outside of the tube.

The constant C introduced in equation (2) determines penalties to estimation errors. A large C assigns higher penalties to errors so that the regression is trained to minimize error with lower generalization while a small C assigns fewer penalties to errors; this allows the minimization of margin with errors, this leads to a higher generalization ability. If C goes to infinity, SVR would not allow any errors to occur and result in a complex model, whereas if C goes to zero, the result would tolerate a large amount of errors and the model would be less complex.

Now, I have solved the value of w in terms of the Lagrange multipliers. For the variable *b*, it can be computed by applying Karush-Kuhn-Tucker (KKT) conditions which, in this case, implies that the product of the Lagrange multipliers and constrains has to equal zero:

$$\begin{aligned}\alpha_i(\varepsilon + \zeta_i - y_i + (w, x_i) + b) &= 0 \\ \alpha_i^*(\varepsilon + \zeta_i^* + y_i - (w, x_i) - b) &= 0\end{aligned} \tag{8}$$

And:

$$\begin{aligned}(C - \alpha_i)\zeta_i &= 0 \\ (C - \alpha_i^*)\zeta_i^* &= 0\end{aligned} \tag{9}$$

where ζ_i and ζ_i^* are slack variables used to measure errors outside the ε-tube. Since α_i, $\alpha_i^* = 0$ and $\zeta_i^* = 0$ for $\alpha_i^* \in (0, C)$, b can be computed as follows:

$$\begin{aligned}b &= y_i - (w, x_i) - \varepsilon \quad \textit{for } \alpha_i \in (0, C) \\ b &= y_i - (w, x_i) + \varepsilon \quad \textit{for } \alpha_i^* \in (0, C)\end{aligned} \tag{10}$$

Putting it all together, SVM and SVR can be used without knowing the transformation.

4. Experiment and Comparisons

4.1. The Selection and the Processing of the Data

In order to evaluate the performance of supply chain management in light of the actual circumstances faced by Harbin Power Equipment Ltd., the paper choose some of the index's fundamental statistics. due to the fact that the data's dimensions and magnitude are different. The index must be quantified since every index in the system needs to be comparable. The supply chain's performance index is divided into two categories: forward direction and backward direction. The equation processed the data in the manner shown below.

$$F_j = (X_j - X_{j\min}) / (X_{j\max} - X_{j\min}) \tag{11}$$

$$F_i = (X_i - X_{i\min}) / (X_{i\max} - X_{i\min}) \tag{12}$$

Where F_i represents the effect coefficient of the X_i, $X_{i\ min}$ represents the minimum value of the No i index, $X_{i\ max}$ represents the maximum value of the No i index, and j represents the number of the index.

After processing , the data are shown in Table 1:

4.2. The Selection of the Parameter

This paper chooses the RBF-kernel. There are only two free parameters, namely and. It is a well known fact that the performance of SVMs is not sensitive to the parameters.

Improper selection of the two parameters can cause either over-fitting or under-fitting of the training data. All of the parameters are selected empirically. It is a difficult task to obtain an optimal combination of parameters that will produce the best prediction performance

Table 1: The Quantification Table of the Sample Data

performance index	1	2	3	4	5	6	7	8	9
Return on capital of supply chain	0.983	0.99	0.654	0.846	0.925	0.967	0.94	0.960	0.000
Inventory at the supplier level	0.763	0.56	0.539	0.631	0.873	0.603	0.85	1.000	0.853
Cash turnover	0.105	0.48	0.065	0.180	0.175	0.000	0.00	0.071	0.067
Customer sell growth	0.815	0981	0.891	0.709	0.613	0.501	0.68	0.849	0.000
Valid time in advance rate	0.375	0.37	0.375	0.500	0.250	0.750	0.25	0.000	0.625
Time soft	0.115	0.71	0.528	0.901	0.350	0.389	0.331	0.259	1.000
Target cost arrived ratio	0.000	0.50	0.500	0.500	1.000	0.500	1.000	0.500	0.500
New product selling rate	1	1	1	1	1	1	1	1	1
Carrying cost	0.051	0.30	0.320	0.771	0.410	1.000	0.529	0.359	0.535
The final assemble place of the product	0	1	1	0	1	1	1	1	1
Involvement of the team	0.244	0.61	0.527	1.000	0.475	0.553	0.538	0.561	0.511
Information sharing rate	0.223	0.22	0.413	1.000	0.683	0.803.	0.698	0.700	0.609
Total cycle period of order	0.261	0.32	1.000	0.430	0.703	0.780	0.735	0.700	0.969
Customer satisfaction	0.005	0.02	0.070	0.205	0.096	0.083	0.093	0.140	1.000
Customer value ratio	1	1	1	1	1	1	1	1	1
Customer retention	1	1	1	1	1	1	1	1	1
Actual assessment result	0.15	0.50	1.00	0.40	0.90	0.60	0.75	0.85	0.95

Continued table

	10	11	12	13	14	15	16	17	18
Return on capital of supply chain	0.990	0.98	1.000	0.991	0.919	0.995	0.997	0.993	1.000
Inventory at the supplier level	0.735	0.90	0.781	0.093	0.939	0.410	0.000	0.411	0.339
Cash turnover	1.000	0.41	0.071	0.071	0.344	0.995	0.997	0.993	1.000
Customer sell growth	0.970	1.00	0.963	0.963	0.813	0.961	0.971	0.957	0.948
Valid time in advance rate	0.000	0.25	0.191	0.311	0.880	0.061	0.250	0.250	0.269
Time soft	0.093	0.00	0.151	0.000	0.061	0.109	0.217	0.061	0.070
Target cost arrived ratio	0.500	0.50	0.500	0.000	0.000	0.500	0.000	0.000	0.000
New product selling rate	1	1	1	1	1	1	1	1	1
Carrying cost	0.048	0.19	0.191	0.000	1.000	0.411	0.221	1.000	1.000
The final assemble place of the product	1	0	0	1	1	0	1	1	1
Involvement of the team	0.000	0.24	0.239	0.211	0.000	0.247	0.000	0.000	0.000
Information sharing rate	0.000	0.22	0.227	0.225	0.000	0.301	0.225	0.220	0.211
Total cycle period of order	0.329	0.49	0.485	0.000	0.095	0.271	0.327	0.325	0.331
Customer satisfaction	0.000	0.02	0.003	0.002	0.003	0.003	0.003	0.005	0.004
Customer value ratio	1	1	1	1	1	1	1	1	1
Customer retention	1	1	1	1	1	1	1	1	1
Actual assessment result	0.10	0.25	0.25	0.20	0.30	0	0.30	0.25	0.25

Since there is a lack of a structured way to choose the free parameters of SVMs, experiments are carried out to investigate the vari-ability in performance with respect to the free parameters. This paper has experimented many times until to get the more accurate result.

4.3. The Selection of the Parameter

This paper chooses the RBF-kernel. There are only two free parameters, namely and. It is a well-known fact that the performance of SVMs is not sensitive to the parameters. Improper selection of the two parameters can cause either over-fitting or under-fitting of the training data. All of the parameters are selected empirically. It is a difficult task to obtain an optimal combination of parameters that will produce the best prediction performance. Since there is a lack of a structured way to choose the free parameters of SVMs, experiments are carried out to investigate the variability in performance with respect to the free parameters. This paper has experimented many times until to get the more accurate result.

4.4. Result and Analysis

From the top to the lowest levels, divided into five levels of factor to take into consideration using performance, the best outcomes of the performance appraisal for 1, subject to a minimum of 0. This is shown in Table 2:

18 samples in all, with samples ~3, 5~11, 13~15, and 17~18 used as training samples and samples 4, 12, and 16 used as validation samples to assess how well the training network worked.

The supply chain performance of Harbin Limited was analyzed using models to create above a specific piece of power equipment. The evaluation yielded a score of 0.8326, and Table 2 shows that the company's supply chain performance is Good. The results of the evaluation and the company's actual situation line up. Harbin Ltd. a power equipment supply chain performance evaluation not only showed that the models for supply chain performance evaluation are reliable and accurate, but also further improve the company's supply chain performance provided valuable guidance.

Table 2: Supply Chain Management Performance Evaluation Factor Table

Performance rating	Performance rating factor
Better	0.8-1.0
Good	0.6-08
Average	0.4-0.6
Poor	0.2-0.4
Poorer	0-0.2

5. Conclusion

Despite the fact that it is still an evolving technology, support vector machines continue to hold great promise for practical applications and major improvements in supply chain performance assessment practice. The paper has suggested several aspects to which support vector machines can have significant contribution. Use of the support vector machines model for enterprise supply chain management performance indicators for the evaluation is feasible, the identification of impact supply chain management performance factors is possible, and there are enough data that are accurate and reliable samples for the SVM study. Using the support vector machines will also result in a more accurate assessment of the practical and indicators for optimizing the business supply chain management to improve performance, logical design. The research results show that the use of support vector machine method for supply chain performance evaluation can supplement the shortcomings of other evaluation methods. This paper expands the application field of support vector machine method and provides theoretical support for optimizing supply chain performance evaluation. Since this study only focuses on the case of Harbin Electric Power Equipment Company, the robustness of the research conclusions needs to be further tested. In the future, the research object will be expanded to test the universality of the research conclusions.

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